A Forecasting Model of Success at the Euro Tournaments: The Role of Team's Performance at Qualifying Games

Ricardo Santos
Trinity University

The European Football Championship (Euro) is different from any other soccer competition in the world in that it has a long and homogeneous qualifying period for all teams. Using data from every tournament that has taken place in history, a step logit model is estimated to quantify the role of team's earlier qualifying performance in the likelihood of success at the final stage. Considering only the information available at the date preceding each of the last three Euros, we test the model's ability to forecast the winner at future tournaments. The model correctly predicted Spain to win it in 2008 and 2012, as well as Portugal to take the Cup in 2016. Teams' efficacy during qualification is found to be a key contributor to the model's forecasting performance.

Our results have strong implications about the current FIFA ranking system as a way to gauge teams' relative strength, as well as about which information a sophisticated bettor should process in order to beat the odds and make a profit out of the betting market. In that regard, we conclude that the betting market is possibly not efficient when pricing teams at the Euros.

Keywords: Forecasting, European Football Championship, Logit, Sports Betting, Market Efficiency

INTRODUCTION

The two biggest national team soccer competitions are the World Cup and the European Football Championship (Euro). The first one gathers the best nations in the world to compete for the trophy, while the second includes only the subset of top European teams. They alternate every other 2 years, and before the first game kicks-off, there is a worldwide discussion about who is going to be the winner. The assessment of who is strongest or weaker is taken more seriously by the Fédération Internationale de Football Association (FIFA), who organizes and designs the rules of the sport, and by bookmakers. The latter can be seen in the betting odds made available to the general public, while the former is reflected in FIFA's national team ranking. The ranking is off great importance because it is used to determine teams seeding for the tournament draw affecting directly the way teams are grouped and their probabilities of victory. Researchers have also been adding to the discussion, particularly with contributions about modelling outcomes in sports.[1] Often these studies focus on the World Cup, the most watched sports event on the planet. It is our goal in this paper to estimate an alternative model and add to that discussion by focusing in the Euro instead - we hope to identify and quantify the role of relevant information in the forecast of the winner in this environment.

Differences between the Euro and the World Cup justify the importance of this analysis. First, the qualifying stage is far more homogeneous at the Euros since in the World Cup teams from different regions follow different rules and diverse qualifying procedures (for example, teams from Africa qualify with 8 games while European soccer nations need to play at least 10 matches, and the ones from South and Central America are required to play up to 18).[2] Thus, studying the Euro allows us to investigate the role of teams qualifying performance in the forecasting exercise, something necessarily missing when studying the World Cup. Second, the shorter duration of the final stage together with a higher concentration of good teams, leaves to chance a bigger role in the final outcome of the competition making the forecasting exercise harder at the Euros.[3] The Euro is also important on its own right. UEFA reports that there were 284 million viewers worldwide for the final of the last tournament. Though it is below the numbers achieved by the World Cup final or the Summer Olympics opening ceremony, viewership of the Euro beats those obtained by the top game in other sports as in the 2017 Super bowl (111.3 million), the 2017 NBA finals (20.4 million), or 2017 MLB World Series (18.7 million). UEFA research reports that the Euro 2016 attracted a cumulated audience of about 2 billion viewers.

We gathered data from all Euros that took place in history (it started in 1960, through 2016). There is information about teams qualifying performance (wins, draws, losses, goals scored for and against in each game) as well as other teams specific variables (team and coach experience, distance to the host nation, number of star players on the team). A step logit model is estimated to quantify the role of teams qualifying performance (as well as the other observables) in the likelihood of success at the final stage. Each step regression corresponds to a specific tournament where only the information preceding that Euro is used. We used the last 3 tournaments to test the model as a forecasting tool. The model correctly identifies all three winners, and teams efficacy (measured by the percentage of wins) during the qualification is found to be a key contributor to the model's forecasting performance. Our results impact what is the relevant information an informed bettor should collect before placing his bets, and FIFA itself when designing its ranking with the purpose of determining teams seeding for the draw. In particular, the presence of star players on the team, the squad's generational cycle, their recent performance on the field, and the distance the team needs to travel to the tournament venue are the four major factors to be taken into account. We are able to find a profitable betting strategy for wagering on Euro tournaments. Therefore, we conclude that the betting market is likely not efficient in this environment.

In Section II we place our article in perspective to related literature and emphasize our contributions. In Section III, we briefly describe the data and present summary statistics. Section IV presents the econometrical model with the calculation of marginal effects. In Section V, betting market odds are introduced and profitable betting strategies identified. Section VI concludes.

RELATED LITERATURE

This paper contributes to the literature of modeling outcomes in sports. With particular emphasis in soccer, early research on the topic focused primarily on modeling goal scoring using Poisson and negative binomial distributions. Moroney (1956) and Reep et. al. (1971) are the earliest examples, but more recently this approach can be found in the works of Dixon and Coles (1997), Koopman and Lit (2015), Rue and Salveson (2000), and Crowder et. al. (2002). Final game results are derived indirectly by aggregating the estimated probabilities assigned to the permutations of goals scored and conceded by the two teams. A second more direct approach makes use of discrete choice regression models such as logit or probit. Match or tournament results are modeled directly, rather than through scores. Koning (2000), with focus in the competitive balance in Dutch soccer, estimates a model that describes results ex post. Kuypers (2000), estimates an ex ante forecasting model using a variety of explanatory variables from English soccer from the 1993-94 season. Forrest and Simmons (2000a,b), evaluate the forecasting performance of newspapers. In his work, Goddard (2005) compares the forecasting performance of these two approaches and finds it to be rather close. With fewer parameters required, and simpler estimation procedures, an emphasis on results rather than scores is preferable. That is the approach adopted in our paper. One novelty of our work is that the regression model is not specific to one single tournament or one league in a given year. Instead, our analysis covers 1960-2016 (15 tournaments), making our results less dependent on season specific events, and therefore increasing the forecasting value of the model towards future tournaments as well.

Several previous studies found the FIFA ranking useful as a predictor of match results in international football (Dyte and Clarke (2000) with focus in the 1998 World Cup, Hoffman et. al. (2002) and Torgler (2004) studying the World Cup of 2002, and Goddard and Thomas (2006)) with the Euro 2004). McHale and Davis (2007) evaluate whether the ranking's methodology from 1998 and 2006 uses information on past results efficiently. They reject that notion by testing the ranking's efficacy in a forecasting model. Our study adds to this literature in that it confirms, under a different environment, that there is the need for modifications in the ranking. We conclude that, in spite of the current rating correctly taking into account recent team performance, information about the presence of star players, the team's generational cycle, and distance are missing. The omission of these important variables weakens the ability of the FIFA ranking to gauge team's quality. The importance of the ranking is that not only determines team's seeding for each tournament draw, but is also used by the UK government to determine a player's eligibility to be granted a work permit.[4] When imposing this condition, the UK government is assuming the ranking is a sufficient guide of team's relative strength, and that no information is missing in the formula.

Forecasting match results is also a key concern for the research on sports betting markets. The recent focus in this line of research has been the study of a possible divergence between bookmarkers' odds and true probabilities.[5] Such differences create opportunities for a sophisticated bettor to formulate profitable betting strategies, and therefore imply a violation of the conditions for market efficiency as defined in the work of Fama (1970).[6] Goddard and Asimokoupoulos (2004) using the English league, Goddard and Dobson (2007) using the Scottish league, and Santos (2019) using World Cup data since 1994, all suggest that the standard conditions for betting market efficiency are not satisfied. In our work, we also address the betting market efficiency by analyzing the relationship between bookmakers odds and the corresponding probabilities for Euros between 2008 and 2016. Though the predictive exercise is more difficult at the Euros than the World Cup with luck playing a bigger role in the determination of the winner, our findings suggest profit margins for an investor that are significantly high. We show that a bettor's dominant strategy is to choose the highest ranked team as indicated by our model. Betting $1 in each of the last 3 Euro tournaments would have generated a total net gain of $29.5, an average of $9.80 per tournament.

EMPIRICAL ANALYSIS

The first Euro took place in 1960, and ever since the championship has been awarded every four years. The Union of European Football Associations (UEFA), the European branch of FIFA, organizes the tournament. Virtually every European country (53 for the last tournament) tries to qualify over a two-year period. After qualifying, 24 teams meet for a month in a common venue to dispute the final stage that leads to the trophy.[7] This final stage is currently organized as follows. First, using a draw, nations are distributed into 6 groups of 4 teams each. There are six round robin matches in each group. Then, the top two teams from each group qualify to the second round, together with the 4 best third-placed teams. The first part of the knockout arrangement starts at 16 teams, and proceeds in that format all the way to the final game. Together, it adds to 51 total matches played in the final stage. Table 1 shows the full list of tournaments that took place in the history of the sport, with information about the host nation as well as both finalists. The 15 championships were won by 10 different nations, with Germany and Spain being the most successful ones with 3 titles each. France is the only other multiple winner with two titles, and is also the only host to have ever won it without having to go through the qualification stage (in 1984).[8]

TABLE 1
EURO HISTORY: HOSTS AND FINALISTS

Year	Host	Winner	2nd Place	Year	Host	Winner	2nd Place
1960	France	Russia	Yugoslavia	1992	Sweden	Denmark	Germany
1964	Spain	Spain	Russia	1996	England	Germany	Czech R.
1968	Italy	Italy	Yugoslavia	2000	Netherlands/Belgium	France	Italy
1972	Belgium	Germany	Russia	2004	Portugal	Greece	Portugal
1976	Yugoslavia	Czech R.	Germany	2008	Austria/Switzerland	Spain	Germany
1980	Italy	Germany	Belgium	2012	Poland/Ukraine	Spain	Italy
1984	France	France	Spain	2016	France	Portugal	France
1988	Germany	Netherlands	Russia	2012	12 countries	?	?

We collected data for all tournaments about team's final stage performance (position or stage each team reached in each tournament), results during the qualifying period (games, points, goals scored and conceded), the structure of the event (number of teams playing at the final stage), each team's squad (players and coaches), and the geographic distance between each nation and the host. The final dataset includes variables constructed from that information and that we now introduce:

- *Wins* - percentage of wins the team obtained during the qualification period. It equals the total number of wins divided by the total number of games played.
- *Goals scored* - average goals scored during qualifying games.
- *Goals conceded* - number of goals suffered per game during the qualification.
- *Star* - to capture the role of star players on each team. Star is objectively defined using the FIFA's award for the best player in the globe. The selection of the best player is based on votes by coaches and captains of international teams, as well as media representatives from around the world. From 2010 to 2015, the trophy was called "FIFA Ballon d'Or", and was jointly awarded with the prestigious French magazine *France Football*. Before 2010 and back to 1956, "France Football Ballon d'Or" by the magazine alone was the reference for the award of the best player.[9] For each tournament, we count the cumulative number of star players on each team that finished at a top three position for the award properly weighted by the final rank: top position is worth three points, second place counts two, and the third position is worth one. With this approach we not only have an assessment of which team has a higher quantity of star quality players, but also *how much* better those players are. A team with one star player that once finished third in the ranking is weaker, ceteris paribus, than a team with one star player that once finished first or second in the award.
- *Experience* - the number of Euro tournament participations the team holds preceding the one in analysis. Since experience increases over time, we use for each team in each tournament, the difference between the team's experience and the tournament average. That provides a relative assessment of how experienced the team is relative to its competition.
- *Coach* - number of prior Euro tournaments for the coach. That experience might have been accumulated with different teams.
- *Last3* - this variable equals 1 if the team has played the final game in any of the last 3 tournaments preceding the one in analysis; and equals 0 otherwise. Typically teams go through generational cycles: one generation of good players comes by, plays an average of 3 Euros together, and then a gap of 1 or 2 tournaments emerges with weaker squads (renovation period in that the team starts replacing older with younger prospects). We consider the last 3 tournaments because with the four year gap in between Euros, it adds up to the 12-year professional life of a player.
- *Distance* - distance in kilometers (km) between each participating nation's capital city and the host's.

With a total number of 4 qualified teams from 1960 through 1976, 8 starting in 1980 all the way to 1992, 16 between 1996 and 2012, and 24 in 2016, we have a total of 156 possible observations. However, we drop the host nations that were not required to qualify as one of our goals is to investigate the role of teams' qualifying performance in the likelihood of winning the tournament. That led to 13 fewer observations, including the 1984 winner (France). Table 2 summarizes for each variable, the average value across all tournaments for the winners. Confronting these values with all other teams' average can potentially pinpoint relevant factors that explain success at the Euros.

TABLE 2
SUMMARY STATISTICS

Variable	Winners	Non-winners
Wins	0.76	0.67
Goals scored	2.16	2.10
Goals conceded	0.65	0.70
Distance	1054	1248
Experience	0.46	-0.05
Coach	0.13	0.21
Star	9.70	2.10
Last3	0.27	0.31

Clearly, teams that win the Euro show stronger qualifying performances ahead of the start of the tournament. They win more games than the other teams, score more goals and concede less. While the difference in goals are not substantial, the 0.09 percentage points difference in wins becomes important when taking into account the 9.6 average length of the qualifying process. Winners total 2.7 more points than the other teams, which is about 13% of the total 21 points teams qualify with on a typical tournament. Not shown on the table but another interesting fact found in our sample is that, out of the total 14 tournaments, in 12 occasions the winner had a higher winning percentage than average. On the other hand, in either goals scored or conceded, winners only outperformed an average team in 8 out of the total 14 occasions. It seems that a team's predisposition to attack or defend more than most is not revealing about the potential to win the Euro, but the end result of the game is. Teams that finish the Euro on top have also shown a greater ability to obtain results in the preceding 2 years.

Distance between each participating nation and the host is another variable that can potentially affect the probability of winning the trophy. Travel costs, cultural and physical factors like heat, or higher fan base for teams playing close to the host nation, can play a role in teams' performances. Table 2 shows that winners do have a lower than average distance traveled to the location of the tournament (194 km less). Even though today is significantly easier and faster to commute everywhere compared to 50-60 years ago, adapting to weather conditions and cultural aspects are still challenges teams need to overcome. Those issues are particularly exacerbated for teams that are more different than the host nation, which typically coincide with those geographically more distant as well.

Considering only the 9 Euros post-1980 (because all teams were inexperienced in the earlier Euros), 7 times the winner was more experienced compared to the tournament's average. Nevertheless, the difference in relative experience for winners was less than half of a tournament. As for coaches' experience, both winners and non-winners do not see in it a possible differentiating factor to win the trophy. For instance, in 12 occasions the team that won the Euro had a debuting coach. The second to last row shows the difference in teams' quality emerging from the quality of the players on the squad. We can see that teams that win the trophy have on average 9.7 points with the calculation adopted for the *Star* variable. Teams that did not win the tournament only had 2.1. For perspective, if one simply considers the number of star players (without weighting the rank position of the player as determined by the award), there is an average of 2.3 star players on the winning teams compared to 0.7 on teams that lose the cup.

Winners have more than three times the number of star players on the other teams. The presence of star players on the team is definitely a factor that can potentially influence the probability of winning the Euro. Only Czech Republic in 1976, Denmark in 1992, and Greece in 2004 won the cup with fewer star players than the average.

The generational cycle of the team is expected to play an important role in determining the winner at the Euro. In all 15-tournament history, only in 4 occasions the winner has managed to be at the final game in any of the previous three tournaments. And two of these cases came precisely in the last two Euros (Spain in 2012 after having played and won the 2012 final, and Portugal in 2016 after losing to Greece in the 2004 final). In the next section, we introduce the econometric model. The model is useful in that it facilitates the quantification of the contribution of each factor in predicting Euro success, and also for an analysis of the efficiency of the betting market.

FORECASTING MODEL

We want to estimate the probability of winning the Euro. Since the outcomes are binary (a team either wins it or not), a model of discrete choice is appropriate. Assume that probability is given by γ, and that it is a function of a vector of explanatory variables X and some unknown vector of parameters β,

$$\gamma(S|X) = E[S|X] = F(\beta X) + \varepsilon,$$

where $S = 1$ for a team that wins it all, or instead $S = 0$ for a unsuccessful Euro campaign. $F(.)$ is the cumulative logit distribution function and ε is an error that is *i.i.d.* across teams and tournaments:

$$F(\beta X) = e^{\beta' X}/(1 + e^{\beta' X}) \tag{1}$$

With the logit distribution, we have the following probabilities:

$$\begin{aligned} \gamma(S = 0 \mid X) &= F(\mu - \beta' X) \\ \gamma(S = 1 \mid X) &= 1 - F(\mu - \beta' X) \end{aligned} \tag{2}$$

with μ being a parameter to be estimated along with β. The list of regressors includes the variables described in the previous section (*Wins, Goals scored, Goals conceded, Distance, Experience, Coach, Star, Last3*), and also the variable *fs-teams*. This variable summarizes the number of teams participating in the final stage of each tournament, and it is included to capture the increased difficulty to become champion that arises with the fact that the number of teams playing the competition have increased over time. Table 3 presents results for three regressions. In each, all information available preceding that specific tournament is used (all Euros prior to 2008 for *reg 08*, Euros prior to 2012 for *reg 12*, and tournaments preceding 2016 for *reg 16*). This step procedure allow us to test the model as a forecasting tool for these last 3 Euro Cups.

TABLE 3
REGRESSION RESULTS

Variable	*reg 08*		*reg 12*		*reg 16*	
	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
Wins	9.6	2.11**	10.5	2.27**	11.9	2.64**
Goals Scored	-1.0	-1.13	-1.2	-1.28	-1.2	-1.37
Goals Conceded	0.7	0.43	0.9	0.55	0.9	0.54
Star	0.2	0.27**	0.3	3.00**	0.3	3.39**
Experience	0.1	0.43	0.3	1.03	0.3	1.18
Coach	0.1	0.03	-0.1	-0.07	-0.6	-0.48
Last3	-1.7	-1.34	-2.1	-1.71*	-1.8	-1.78*
Distance	-0.004	-2.33**	-0.003	-2.22**	-0.004	-2.27**
Distance^2	0.0	2.24**	0.0	2.17**	0.0	2.34**
fs-teams	-0.0	-0.24	-0.0	-0.25	-0.0	-0.23
μ	-5.4	-1.56	-6.0	-1.71*	-7.2	-2.20**
Euros used	60-04		60-08		60-12	
# obs	92		106		120	
LR-stat (10)	26.1		30.4		34.6	

* / ** means the variable is statistically significant at 10% / 5% confidence level respectively

Results confirm the earlier empirical analysis. A stronger qualifying performance as indicated in the percentage of wins has a positive and statistically significant impact on the probability of winning the cup. Qualifying performance indicated by either goals scored or conceded are not statistically significant and do not help single out winners. The other relevant factors in determining winners are the presence and quality of the star players on the team, not having to travel as much to the tournament location, and having a generation of players that is reaching its peak (ie, not having reached the final in any of the last 3 tournaments). From Table 3 it can also be seen that, the larger the tournament sample used, the stronger the statistical power of our model. Nevertheless, all three regressions pass the Likelihood Ratio Chi-Square Test.

Using these coefficients, we can fit the model back to the data used in the estimation and obtain the model's prediction for the winner of each of the tournaments. Table 4 shows the results of this exercise. Nothing shows in 1984, as the winner and host (France) was not included in the analysis - as pointed out before, since 1980 we dropped observations regarding hosts because they do not need to go through the qualifying stage.

TABLE 4
MODEL'S FIT FOR 1st POSITION
(THE ACTUAL FINAL POSITION IS SHOWN IN PARENTHESIS)

Year	*reg 08*	*reg 12*	*reg 16*
1960	Russia (1)	Russia (1)	Russia (1)
1964	Spain (1)	Spain (1)	Spain (1)
1968	Italy (1)	Italy (1)	Italy (1)
1972	Germany (1)	Germany (1)	Germany (1)
1976	Netherlands (SF)	Netherlands (SF)	Netherlands (SF)
1980	England (GS)	England (GS)	England (GS)
1984	---	---	---
1988	Netherlands (1)	Netherlands (1)	Netherlands (1)
1992	Netherlands (SF)	Netherlands (SF)	Netherlands (SF)
1996	Germany (1)	Germany (1)	Germany (1)
2000	France (1)	France (1)	France (1)
2004	Spain (GS)	Spain (GS)	England (GS)
2008	---	Spain (1)	Spain (1)
2012	---	---	Spain (1)

The model correctly matches the winner in 7 out of 11 occasions / 8 out of 12 / and 9 out of 13. In any of the three regressions, the misses are with the Euros of 1976, 1980, 1992, and 2004. To reflect on the model's miscues, Czech Republic (winner in 1976) and Germany (won it in 1980) appeared at the final stage with a lower percentage of wins than their opponents did. These teams' predicted model probabilities were also dampened by a low number of star players (in the case of the Czech team), or because the team had played a final in any of the last 3 tournaments (for the case of Germany). As for Denmark in 1992 and Greece in 2004, the crucial reason why the model ranks these winners below other teams is a low number of star players. They had exactly zero. On top of that, there was an interesting context surrounding each of these teams. Greece had never won a single game at the final stage preceding the Euro 2004, and their experience at this type of events was almost negligible. As for Denmark, they did not even qualified at first. They were invited to replace Yugoslavia due to the breakup of warfare in the region. Danish players were already on vacation when called up 11 days ahead of the start of the tournament! As in our model, nobody in the soccer world would imagine either of those winners to go all the way and win the cup.

By calculating the marginal effect of each observable, we can quantify the role they play in the determination of success at the final stage. Table 5 shows the average marginal effects from changes on the regressors that were statistically significant with our regression. All numbers are percentage point differences except for the last row that presents the benchmark probability of winning the trophy. For the *Wins* variable, the marginal effect is the equivalent in the winning percentage of the difference in the probability of winning the Euro when the team makes one extra win during the qualification (for instance, in our benchmark regression teams qualify on average with wins in 68.2% of their games; one extra wins would then represent winning 79.7% of those matches). In the *Star* case, the marginal effects reflect the impact of having an extra player that was awarded 3^{rd} place (+1 point in *Star*) and 1^{st} (+3 points in *Star*) in the FIFA's selection for the best player in the World. As for *Last3*, the effects concern the percentage points difference obtained when the team has played an Euro final in the past 3 tournaments, and when it has not. Finally, the marginal effect for *Distance* captures differences in the probabilities of victory that are calculated using the average distance (in km), and 15% on top of that average (200 km more).

TABLE 5
MARGINAL EFFECTS

Variable	*reg 16*
Wins	9.6
Star (+1)	1.8
Star (+3)	6.2
Last3	-10.6
Distance	-3.4
Benchmark	10.8

The table shows how important team's performance at the earlier qualifying stage is in predicting success for the final stage. Teams that come out strong from qualification practically double their chances of victory. By the time the tournament starts, the team's confidence is already high, the players are connecting well on the field, and coaches already believe in their approach to the game, so there will not be much strategic work to do. If instead, the team barely qualifies, much is discussed on which players should or not be called up to the final stage, whether the style of play was appropriate, confidence amongst players is not as high...[10]

Having one more good player that finished 3rd in the FIFA's nomination does not play a very strong impact in the probability of lifting the trophy, but the same cannot be claimed when comes to having a superstar (a player that finished 1st in the same nomination). Teams with a top player on their team had 6.2 more percentage points in the chances of winning the Cup compared to a team with average star quality. Some of the most recent winners that had players on the team who were at some point the best player in the world include Portugal in 2016 (Cristiano Ronaldo), France in 2000 with Zinedine Zidane, Germany with Matthias Sammer in 1992, and Netherlands in 1988 with both Marco van Basten and Ruud Gullit. Spain won the Euro in both 2008 and 2012 without a player ever being nominated 1st, but included in their squads Xavi Hernandez (three times 3rd place) and Andres Iniesta (a second and one third place nomination).

Getting to the final stage with a generation of players that is peaking (*Last3=0*) also has a strong impact on the chances of winning - it doubles it up! That was already evident from the empirical analysis. In the first 50 years of the tournament's history, only Germany managed to play a final after having done so in any of the last three Euro Cups (in 1980 and 1996). Portugal and Spain are the only other two exceptional occasions (2012 and 2016 respectively). Among the four key factors in the determination of success, distance has the most subtle effect. Nevertheless, avoiding long travels can also benefit a team's chances of victory. Europe is a small Continent, and distance here is most likely capturing cultural proximity between countries. Playing in a venue where weather and culture are more alike to a team's native country improves their chances of winning by 3.4 percentage points.

Model as a Forecasting Tool

The most ambitious test of the model is predicting correctly the winner at future tournaments. With team statistics for each tournament, together with the model coefficients, teams' winning probabilities can be obtained and ranked. Table 6 shows for each of the last three Euros, the model prediction for the project winner and the corresponding predicted probability. Impressively, in all three occasions, the model gets it right.

TABLE 6
ACCURACY TEST

Year	Actual	Model	FIFA	Bookmakers
2008	Spain	Spain (35%)	Italy	Germany (17%)
2012	Spain	Spain (29%)	Spain	Spain (29%)
2016	Portugal	Portugal (43%)	Belgium	Germany (23%)

For contrast, the table also shows the FIFA's highest ranked team at the start of each tournament, and bookmakers' favorites to win it all. The latter is found using average odds from the 3 bookmakers that we used in the analysis presented in the next section (3 for each of the Euros). FIFA's top ranked team only coincides with the actual winner once.

In 2008, Spain was ranked 2*nd* highest behind Italy, and in 2016 Portugal was ranked 4*th*. Note that our model does better than the FIFA ranking despite their inherent advantage. Their ranking is used to determine tournament seedings. Thus, even if they are not very accurate, higher ranked teams would have a better chance to do better because they get an easier path to the finals. In other words, the FIFA ranking is in part self-fulfilling, while our model's predictions are obtained without that edge or even without considering team placement.

The model's forecasting ability is also superior to predictions made out of bookmakers' favorites. As with FIFA top ranked team' prediction, they only get it right in 2012, and miss it in 2008 and 2016. Germany was bookmakers' favorite in both of those occasions, having come closed with a second place finish in 2008 and being eliminated in the semi-final game in 2016. Actual winners were not priced as high in either occasion (Spain was still a high 2*nd* favorite in 2008, but Portugal only come in 7*th* in 2016).[11]

BETTING MARKET EFFICIENCY

In this section, we investigate the efficiency of the odds posted by several bookmakers for bets on the outcome of the Euro tournament. The odds are compiled directly from online betting exchange places such as William Hill, Ladbrokes, and Coral for 2008, William Hill, Ladbrokes, and SkyBet for 2012, and William Hill, Coral, and SkyBet for 2016. Bookmakers' odds are typically quoted in fractional form *a/b*, where *b* is the stake on a team to win the tournament and *a* is the net return made from that bet. The bettor collects a total of (a + b) if the bet wins (the bookmaker pays the winnings and returns the stake), and makes $-b$ if loses (the bookmakers keeps the stake). These odds can be converted into winning probabilities for each team (i) in the form $\theta_i = b/(a+b)$. A necessary condition for all the n possible winning bets on a tournament to be "fair" had to produce a joint expected return of zero amongst the bookmaker and the bettor, that is $\sum_{i=1}^{n} \theta_i = 1$. However, the payout to a successful bettor is typically less than what would be represented by the true chance of all events occurring. Bookmakers include a profit margin when formulating the odds called the over-round (λ), where $\lambda = (\sum_{i=1}^{n} \theta_i) - 1$.

Since bookmakers typically use similar, but not exactly equal odds for the same bet, a bettor who is willing to shop around for the most favorable odds in each bet has an arbitrage opportunity. Table 7 shows for each tournament the over-round found under "best" ($\tilde{\lambda}$) and "median" ($\hat{\lambda}$) odds. The first column reflects the best available odds from all available bookmakers for each team in each tournament. Formally, denote by J the vector of available bookmakers for a given tournament. Then, $\tilde{\theta}_i = min_{j\epsilon J}\left(\theta_i^j\right)$ summarizes the best available odds for each team $i \in \{1,..,n\}$ in that year. These are the odds a bettor who shops around would find. In this case, the bookmaker's profit margin is found by $\tilde{\lambda} = (\sum_{i=1}^{n} \tilde{\theta}_i) - 1$. The second column, concerns median odds from the set of bookmakers used in that year, and are representative of the odds available for a bettor who does not shop around. Now, $\hat{\theta}_i = median_{j\epsilon J}\left(\theta_i^j\right)$, and $\widehat{\lambda} = (\sum_{i=1}^{n} \hat{\theta}_i) - 1$. It is very clear from the table, that a bettor willing to browse the odds before placing his bet could significantly eliminate the proportion of the negative contribution made by bookmakers' margins in the expected return. For 2008 and 2012, the profit margin is cut by a factor of 3 and 2 respectively. In 2016, it is 5 times lower. This finding aligns with the previous literature (see Goddard and Dobson 2007 as one prime example), and as such it increases our confidence in that our random selection of bookmaker odds is representative of this betting market.

TABLE 7
BOOKMAKER'S OVER-ROUND

Year	Best odds	Median odds
2008	0.02	0.06
2012	0.12	0.20
2016	0.01	0.05

If bookmakers' odds fail to reflect all publicly available information, then the opportunity to find a profitable betting strategy emerges. We investigate this possibility by examining the net returns from a single \$1 bet under three different criteria. The first criterion is to select bookmakers' favorite team as indicated in the odds offered, the second is FIFA's top ranked team in the month preceding the start of the tournament, and the third criterion is to pick the team ranked top as indicated by our model. For the latter, let $(\tilde{a}, \tilde{b})_i$ be the pair that summarizes respectively the winnings and the stake available at best odds for team i, and γ_i the model probability of winning the WC in that year (found using (2)). Then, team's i expected return is given by:$E[R_i] = (\tilde{a}_i/\tilde{b}_i).\gamma_i + (-1).(1-\gamma_i)$. The bet selection shown in the last column of Table 8 is found with $\max E_i[R_i]$.

Table 8 displays the bet selection under each of the three criteria, and their respective net return. The table also lists actual tournament winners. Our results are very clear in that the dominant strategy for a bettor placing a single \$1 bet is to follow the model's predictions. In each of the tournaments, all booking houses in our sample agreed on the team that would be on top, but only got it right once in 2012 with Spain. The sum of net returns for the 3 tournaments is yet positive, but very low (\$0.5). FIFA's top ranked team won the Euro in 2008, and lost in the other two occasions. The sum of net returns is again \$0.5. On the other hand, following the model predictions would have never resulted in a loss. All three Euros combined yielded a total net gain of \$29.5, an average of \$9.8 per competition, clearly above any of the other two strategies considered.

TABLE 8
TEAMS SELECTED FOR A SINGLE \$1 BET, AND RESPECTIVE NET RETURNS

Year	Winner	Best odds	FIFA	Model
2008	Spain	Germany (-1)	Italy (-1)	Spain (+7)
2012	Spain	Spain (+2.5)	Spain (+2.5)	Spain (+2.5)
2016	Portugal	Germany (-1)	Belgium (-1)	Portugal (+20)
Sum of net returns		+0.5	+0.5	+29.5

Next, we consider scenarios where the bettor places multiple bets. We only focus on multiple bets using the FIFA ranking or bookmakers' prices as criteria. It is innocuous to consider the model since it would always result in returns below those obtained under the \$1 single bet on the winner - the model's forecasted winner was always correct. Both the FIFA ranking and bookmakers' probabilities got it right in 2012, and placed the actual winner (Spain) in 2008 as the 2^{nd} highest likely to win. The major difference between the two comes in 2016: FIFA ranked Portugal 4^{th}, while bookmakers' average odds had the Portuguese team only 7^{th}. The table below summarizes our findings under multiple bets. It is evident that acquiring lower risk under either of these two criteria could result in interesting payoffs ($10.5 for best odds, and $19.5 with FIFA), above those obtained under single $1 bets.

TABLE 9
WINNER'S RANKS AND MULTIPLE BETS

Winner's Ranks	2008	2012	2016
Best Odds	2^{nd}	1^{st}	7^{th}
FIFA	2^{nd}	1^{st}	4^{th}

Total Net Returns	Top 2	Top 4	Top 7
Best Odds	+5.5	-0.5	+10.5
FIFA	+5.5	+19.5	+10.5

In conclusion, our findings suggest that the betting market in professional football is possibly not efficient. With basis on the last three Euros, a sophisticated bettor could formulate profitable betting strategies. In particular, we find that:

- shopping around for better odds among the different booking houses can minimize, and in some years, almost completely eliminate bookmaker's over-round;
- a "blind" bet on bookmakers or FIFA's top 2 ranked teams prior to the start of the tournament results in already significant returns ($1.83 per Euro); yet FIFA's top 4 and bookmakers' top 7 were the profit maximizing strategy under each of these two criteria respectively;
- the dominant, profit maximizing strategy for an investor is to follow the model's highest expected return team and choose a single team bet (net return of $9.8 per tournament).

CONCLUSION

The European Football Championship (Euro) is one of the two most important soccer competitions in the history of the sport. It is different from any other in that it has the highest concentration of high quality teams amongst participants (since the implementation of the FIFA ranking in 1993, the median ranked team in the Euro ranks on average 6 positions better than that of the World Cup). That makes forecasting the winner in this environment an extraordinary task because almost any team can have a good stream of 6-7 matches and come out with the trophy. In only 15 tournaments, there were 10 different teams winning the trophy; as comparison, in the World Cup there is a total of 20 events with just 8 different winners. A second peculiar feature of this tournament is that it requires teams to go through a homogeneous and long qualifying stage before playing the tournament. The two-year long qualifying period can be used to infer about teams current form going in to the final stage, something necessary missing in most sports forecasting literature that focus on the World Cup.

In this study, we used data from all the Euros in the history of the competition (19602016), and estimated a step logit model to forecast the likelihood of success for each team in each tournament. By using a large set of tournaments, our model predictions are not tournament or year specific and can be used in forecasting exercises regarding future tournaments as well. The model correctly identifies the winner in 10 out of 14 events. Teams' winning percentage during the qualification, the weighted presence of star players in the squad, the geographic distance between each nation and the host, and the squad's generational cycle are the key contributors to winning the tournament. The most ambitious test of the model is its forecasting success rate. We obtained and ranked each team's probability of winning the Euros of 2008, 2012, and 2016. The model got it right for all three tournaments tested. Alternatively, predicting the winner by using FIFA's highest ranked team, or a rank made out of bookmakers' odds got it correct only once.

In the final part of the analysis, we used bookmakers' odds and model probabilities to identify a betting rule that delivers positive net returns. We find that choosing the team with the model's highest expected return at best odds would have generated an average net return of $9.8 in the last 3 tournaments. For instance, in the last Euro alone, a bettor could have made a $20 profit out of each dollar invested. For comparison, a bet with basis on bookmakers' favorite team, or FIFA's top ranked team, would have resulted on an average net return of only $0.17 in those same 3 Euros (and with losses coming in two of the three). These results provide some evidence that bookmakers are not making use of all available information in the formulation of their odds. They hint at the possibility of rejecting the hypothesis of the Euro betting market being efficient as defined in the work by Fama (1970). With the soccer betting industry already at approximately $600 billion, the importance of our findings are magnified, and could even lead to a revision of the method used to formulate the odds currently adopted by bookmakers.[12,13]

One thing is certain; an informed bettor that is trying to capture a slice of the $600 billion should definitely monitor how teams got to the Euro's final stage. Teams that barely qualified are likely engaged in long discussions about squad selection, tactical system, and team line-up. Those teams will struggle at the final stage. For teams that went through a strong qualifying period, most of the players and staff energy will be spend on getting everyone fit and studying opposition. Those are the teams an investor should keep his eyes (and his money) on. For instance, a team that shows to be in better form as indicated by its performance during the qualifying stage (one more victory than average, which represents 80% wins of the total number of games compared to the 68% counterpart), nearly doubles the likelihood of winning the final stage (20.4% chances of victory compared to the benchmark probability of 10.8%).

ENDNOTES

1. Literature review on the topic is provided in the next section.
2. For the Euro, the current range of qualifying games is between 8 and 10. Historically, the difference of qualifying games necessary to be at the Euro's final stage was always equal or less than three games.
3. In the Euro 2012, the average FIFA rank of participating teams was 16th. This number would be even lower (indicating stronger teams) if it was not the fact that the host nations (automatically qualified to the final stage) were weaker soccer nations - Poland (ranked 65*th*) and Ukraine (ranked 50*th*). Half the teams in that Euro were below the 12*th* position in the rank, and 75% of the teams were in the top 20. In 2016, the average increased to 19 due to the increase in the number of participating teams at the final stage. For comparison, the last two World Cups had a rank average of 22 and 26, and with the median team being ranked 18*th* and 17*th*.
4. One of the conditions for a soccer player to be granted a work permit in the UK is that "the player's National Association must be at or above 70*th* place in the official FIFA World ranking when averaged over the two years preceding the date of application".
5. In this line of research, the initial focus was to evaluate the existence of systematic biases in bookmakers' odds such as home-away team bias (Pope and Peel 1989) and favorite-longshot bias (Cain et. al. 2000).
6. Fama defines a financial market as efficient if, contingent on the publicly available information at the time of the investment, one cannot consistently achieve an excess market return. If using the forecasting model a bettor can find a profitable betting strategy, then prices (odds) do not reflect all publicly available information.
7. The number of qualified teams started at only 4. In 1980, UEFA increased it to 8, and then again in 1996 to 16 teams. Starting in 2016, the final stage comprises 24 teams.
8. Since 1980, hosts are automatically qualified to the final stage. Before then, the host of the tournament would be determined amongst the 4 qualified teams.
9. Since 2016, FIFA and France Football parted ways and now each holds its own award. That could only play a role in our *Star* variable affecting the 2016 Euro forecast. However, both awards have agreed perfectly in their top three choices ever since their split.
10. There is also an indirect link between a strong qualifying performance and the likelihood of winning the Euro. FIFA assess all teams' relative strength by means of a rank. This rank places a heavier weight on recent performance, and is used to determine tournament seedings. Therefore, teams that did better in the recent year(s) will be ranked higher and get an easier path to the final by a favorable final stage draw.
11. Bookmaker odds are from dates after the final stage draw. Added information about the composition of the groups helps provide a more accurate probability of winning the Euro for each team because the strength of the opponents in the group directly affects the chances of advancing to the playoff round, a necessary occurrence to win the trophy. Since forecasts made without this added information are more difficult to be correct, we see as an advantage the fact that our model is able to consistently predict the actual winner

without using that group stage data at all. Our model's forecasts are good from the moment that all participating teams are found (typically, September on the year preceding the Euro).

12. Sportradar analysts reported in January 2014 that about $700 billion to 1 trillion is spent every year in both legal and illegal sports betting markets, from which soccer takes about 70% of the share.
13. For the US, a study by the American Gaming Association (2012) claims that $3.45 billion was legally wagered in Nevada, and according to the National Gambling Impact Study Commission (1999), there is an additional $380 billion of illegal gambling every year.

REFERENCES

American Gaming Association. (2012, June). Sports Wagering. Fact sheets about sports wagering.

Cain, M., Law, D., & Peel, D. (2000). The Favourite-Longshot Bias and Market Efficiency in UK Football Betting. *Scottish Journal of Political Economy*, 47, 25-36.

Crowder, M., Dixon, M., Ledford, A., & Robinson, M. (2002). Dynamic Modelling and Prediction of English Football League Matches for Betting. *The Statistician*, 51, 157-168.

Dixon, M. J., & Coles, S. C. (1997). Modelling Association Football Scores and Inefficiencies in Football Betting Market. *Applied Statistics*, 46, 265-280.

Dyte, D., & Clarke, S. R. (2000). A Ratings Based Poisson Model for World Cup Simulation. *Journal of the Operational Research Society*, 51, 993-998.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383-417.

Forrest, D., & Simmons, R. (2000a). Forecasting Sport: the Behaviour and Performance of Football Tipsters. *International Journal of Forecasting*, 16, 316-331.

Forrest, D., & Simmons, R. (2000b). Making up the Results: The Work of Football Pools Panel, 1963-1997. *The Statistician*, 49(2), 253-260.

Goddard, J., & Asimokoupoulos, I. (2004). Forecasting Football Match Results and the Efficiency of Fixed-Odds Betting. *Journal of Forecasting*, 23, 51-66.

Goddard, J. (2005). Regression Models for Forecasting Goals and Match Results in Association Football. *International Journal of Forecasting*, 21, 331-340.

Goddard, J., & Thomas, S. (2006). The Efficiency of the UK Fixed-Odds Betting Market for Euro 2004. *International Journal of Sport Finance*, 1, 21-32.

Goddard, J., & Dobson, S. (2007). *Statistical Thinking in Sports*. J. Albert and R. Koning (eds), 91-109.

Hoffman, R. L., Ging, C., & Ramasamy, B. (2002). The Socio-Economic Determinants of International Soccer Performance. *Journal of Applied Economics*, 5, 253-272.

Koning, R. H. (2000). Balance in Competition in Dutch Soccer. *The Statistician*, 49(3), 419-431.

Koopman, S. J., & Lit, R. (2015). A dynamic bivariate Poisson model for analysing and forecasting match results in the English Premier League. *Journal of the Royal Statistics Society*, 178(1), 167-186.

Kuypers, T. (2000). Information and Efficiency: An Empirical Study of a Fixed Odds Betting Market. *Applied Economics*, 32, 1353-1363.

McHale, I., & Davis, S. (2007). *Statistical Thinking in Sports*. J. Albert and R. Koning (eds), 77-90.

Moroney, M. J. (1956). *Facts from Figures*, 3rd ed. Penguin: London.

National Gambling Impact Study Commission. (1999, August). *Final Report*.

Pope, P. F., & Peel, D. A. (1989). Information, Prices, and Efficiency in a Fixed-Odds Betting Market. *Economica*, 56, 323-341.

Reep, C., Pollard, R., & Benjamin, B. (1971). Skill and Chance in Ball Games. *Journal of the Royal Statistical Society*, Ser. A 131, 581-585.

Rue, H., & Salveson, O. (2000). Prediction and Retrospective Analysis of Soccer Matches in a League. *The Statistician*, 49, 399-418.

Santos, R. (2019). FIFA World Cup: A Case of (In)Efficiency of the Betting Market. *Working Paper*.

Torgler, B. (2004). The Economics of the FIFA Football World Cup. *Kyklos*, 57, 287-300.